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Research Paper

Deep Sequential Driver Behaviour Modelling Using LSTM Integrated with Extra Trees for Attrition Prediction

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ABSTRACT

Driver attrition has emerged as a critical challenge for ride-hailing platforms, as it directly affects operational efficiency, service availability, and overall customer satisfaction. Early identification of drivers who are at high risk of leaving the organization enables companies to implement effective retention strategies and maintain workforce stability. Traditional approaches to driver attrition analysis primarily relied on manual surveys, basic statistical techniques, and rule-based decision systems. These methods depended heavily on historical observations and human judgment, offering limited capability to process large-scale and high-dimensional datasets. As a result, such approaches often failed to capture complex relationships and hidden patterns among the factors influencing driver attrition. To overcome these challenges, the proposed system introduces a hybrid deep learning and machine learning architecture. A Long Short-Term Memory (LSTM) neural network is employed to extract meaningful latent features from structured driver data, capturing underlying feature relationships and hidden patterns. These extracted features are then utilized by a Greedy Tree (GT) classifier to perform the final attrition classification, ensuring both high predictive accuracy and model interpretability. For performance comparison, several traditional machine learning models, including Random Forest (RF), Gradient Boosting (GB), and Support Vector Classifier (SVC), are also implemented and evaluated. Experimental results demonstrate that the proposed Greedy Long Short-Term Memory Tree (GLSTMT) model achieves an accuracy of 100%, outperforming the baseline models on the dataset used in this study. The complete system is implemented with a web-based architecture deployed through the Flask framework, which manages model integration, user authentication, and interaction between frontend and backend components.

Keywords: Driver Attrition, Ride-Hailing Platforms, Workforce Stability, Attrition Prediction, Feature Extraction, Latent Features, Pattern Recognition, Classification System, Predictive Analytics.

1. INTRODUCTION

Driver attrition is expressed as the normal process by which the Drivers leave the organization due to some reasons, such as the resignation of Drivers. There are many factors that can cause drivers attrition. The Driver leaves the organization faster than they are hired Fig. 1. When the drivers leave the organization, the vacancies remain unfilled, resulting in a loss for the organization. The driver attrition rate helps to understand the progress level of an organization. The high attrition rate shows that the Driver are frequently leaving. The results of the high attrition rate are the loss of organizational benefits. In order to keep the organization in progress, the attrition rate must be controlled.

Many types of driver attrition help us to understand the attrition process. The attrition type is whether drivers choose to leave the company voluntarily. The involuntary attrition type is when the organization

ends the employment process. The external attrition type is referred to when Driver leaves an organization to work for another organization. Internal attrition occurs when Driver is given another position within the same organization as a promotion. The driver attrition rate is the measure of people who leaves the organization. By measuring the attrition rate, we can identify the causes and factors that need to be solved to eliminate driver attrition. The attrition rate is calculated by dividing the number of Driver who have left the company by the average number of Driver over some time. The attrition rate helps us find the company's progress over a specific period.

Impact of components in driving employee retention	Average economic context	Economic downturn context	Rank difference between contexts
1 (Most Impactful Factor)	Opportunity	Work	+1 More Important
2	Work	People	+1 More Important
3	People	Opportunity	-2 Less Important
4	Rewards	Rewards	No Change in Importance
5 (Least Impactful Factor)	Organization	Organization	No Change in Importance

Fig. 1: Driving Employee Attrition Strategy

The Driver attrition states demonstrate that after six months of job duration, 1/3 of new Driver leave the organization. The 3 to 4.5 million Driver leave their job every month in the United States, according to the Job Openings and Labor Turnover Survey (JOLTS). The driver attrition rate is 57.3% in 2021 to the report of the Bureau of Labor Statistics. The report also suggests that in many industries, the driver attrition rate is close to 19%. The cost per hire of new Driver is USD 4129 by SHRM. Ninety percent of drivers retention rate is considered suitable for a company, and the attrition rate must be less than 10%.

2. LITERATURE SURVEY

Xu et al. [1] empirically studied drivers' response behavior to ride-hailing requests based on data from ride-hailing platforms, and clarified that drivers are more likely to respond to requests with economic incentives. Bandiera et al. [2] present a mathematical model to simulate the interaction between service providers and customers. Xi et al. [3] developed a multi-leader–multi-follower model in which platforms compete to optimize their operations.

Denget al. [4] explored how to optimize the operations of RHPs by investigating the impact of commission rates on drivers' switching behaviors in a dynamic mobility market. Two queue-theory-based mathematical models were developed to examine the relationship between commission rates, drivers' switching behaviors, and critical platform parameters in optimizing the operations of RHPs. Numerical examples were presented to demonstrate the applicability of these models in determining the optimal commission rate to enhance the operations of RHPs under duopoly and fully competitive market conditions.

Cohen and Zhang [5], developed an endogenous model to simulate the operations of two-sided RHPs, leading to the determination of the optimal service price and the most appropriate commission rate in an analytical manner. Sun and Ertz [6] propose a system dynamic modeling framework to explore the ride-hailing operations, discovering that commission rates, order prices, and investment levels are the

critical variables for optimizing the operations of RHPs. Zhong et al. [7] examine how RHPs compete with traditional taxi companies, resulting in designing specific pricing strategies under unregulated and regulated environments in optimizing the operations of RHPs. The studies above have provided insights into how to improve the operations of RHPs from different perspectives.

Sun et al. [8] discovered two types of order assignment strategies have distinct impacts on the operations of RHPs. Xu et al. [9] proposed a generalized fluid framework incorporating appropriate commission rate setting for modeling ride-hailing to improve the operations of RHPs. Ke and Qian [10] developed an optimal pricing scheme for improving the operations of RHPs. Yao and Zhang [11] adopt a many-to-many matching framework for solving the pricing problem that RHPs face in a multi-modal transport network.

Sun et al. [12] investigated the influence of various regulatory policies on the operations of RHPs with respect to the growth of individual platforms. The discussion above has provided a better understanding of how to improve the operations of RHPs from three perspectives. There is, however, a lack of studies on how to achieve a subtle trade-off between platform profitability and customer service quality in optimizing the operations of RHPs. The interplay between commission rates, drivers' switching behaviors, and critical platform parameters in optimizing the operations of RHPs is unclear. There are some limitations in this study. First, there is specific simplification about drivers' behaviors in developing the two mathematical models for optimizing the operations of RHPs in the dynamic mobility market [13]. The variation in the driver quantity for a long time, for example, is not considered. The total driver quantity in the ride-hailing market is assumed to be stable in this study. This can be further explored on the impact of the variation in the total driver quantity on the optimal commission rate. Second, the cooperation between RHPs is not considered. In practice, there usually exists not only competition but also cooperation between platforms, which is taken as a coopetition relationship in aggregated platform contexts [14].

Zhang et al. [15] addressed electric ride-hailing vehicles (ERVs), as a novel mobility paradigm, utilize intelligent platform-based scheduling to improve operational efficiency and create numerous employment opportunities. Contrasted with the traditional fuel-powered ride-hailing vehicle with the average annual carbon emissions of 4.6 tons, pure electric vehicles (PEVs) reduce emissions by 85.71 kg monthly during operation.

3. PROPOSED SYSTEM

The proposed system introduces an intelligent, automated, and data-driven approach for predicting attrition risk using Machine Learning techniques and a web-based deployment framework as demonstrate in Fig. 2. The system replaces manual analysis with a structured pipeline that processes real-time data, learns hidden behavioral patterns, and provides accurate attrition predictions through an interactive user interface.

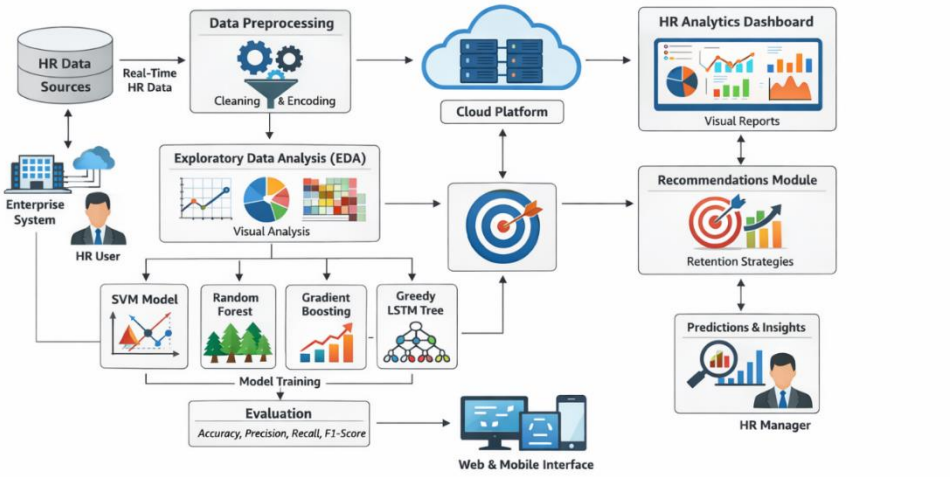


Fig. 2: Proposed system architecture.

Data Collection: Structured datasets are collected containing driver-related attributes such as demographic information, working conditions, job satisfaction levels, performance ratings, and work-life balance indicators. These attributes include factors such as age, job role, monthly income, working hours, job satisfaction score, environment satisfaction, relationship satisfaction, and performance ratings. The collected dataset forms the foundation for training and evaluating the machine learning models used for driver attrition prediction.

Data Preprocessing: The collected dataset undergoes several preprocessing steps to ensure data quality and suitability for model training. Removal of irrelevant and redundant attributes that do not contribute to prediction accuracy. Handling missing or inconsistent data values. Encoding categorical variables into numerical representations using label encoding. Techniques. Feature normalization and scaling to ensure consistent data distribution across attributes. These preprocessing steps improve the reliability and efficiency of the prediction models.

Exploratory Data Analysis (EDA): EDA is performed to understand the characteristics and relationships within the dataset. Statistical analysis and visualization techniques are used to examine attribute distributions, correlations between features, and patterns associated with driver attrition. This analysis helps in identifying important variables and provides insights that support better feature selection and model development.

Feature Selection: Feature selection is conducted to identify the most relevant attributes influencing driver attrition. Important features are selected based on correlation analysis, statistical relevance, and domain knowledge. Irrelevant or weakly related attributes are removed to reduce model complexity, improve computational efficiency, and enhance prediction accuracy.

Model Training: Multiple machine learning algorithms are trained using the prepared dataset to evaluate their performance in predicting driver attrition. These algorithms include RF, GB, and SVC. In addition, the proposed hybrid model GLSTMT for final prediction. The LSTM component extracts meaningful latent features from the dataset, while the GT performs the classification based on these extracted features.

Model Evaluation: The trained models are evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. These metrics measure the effectiveness of the models in correctly identifying drivers who are likely to leave or remain in the organization. Experimental results indicate that the proposed GLSTMT model achieves the highest prediction accuracy compared to the baseline models.

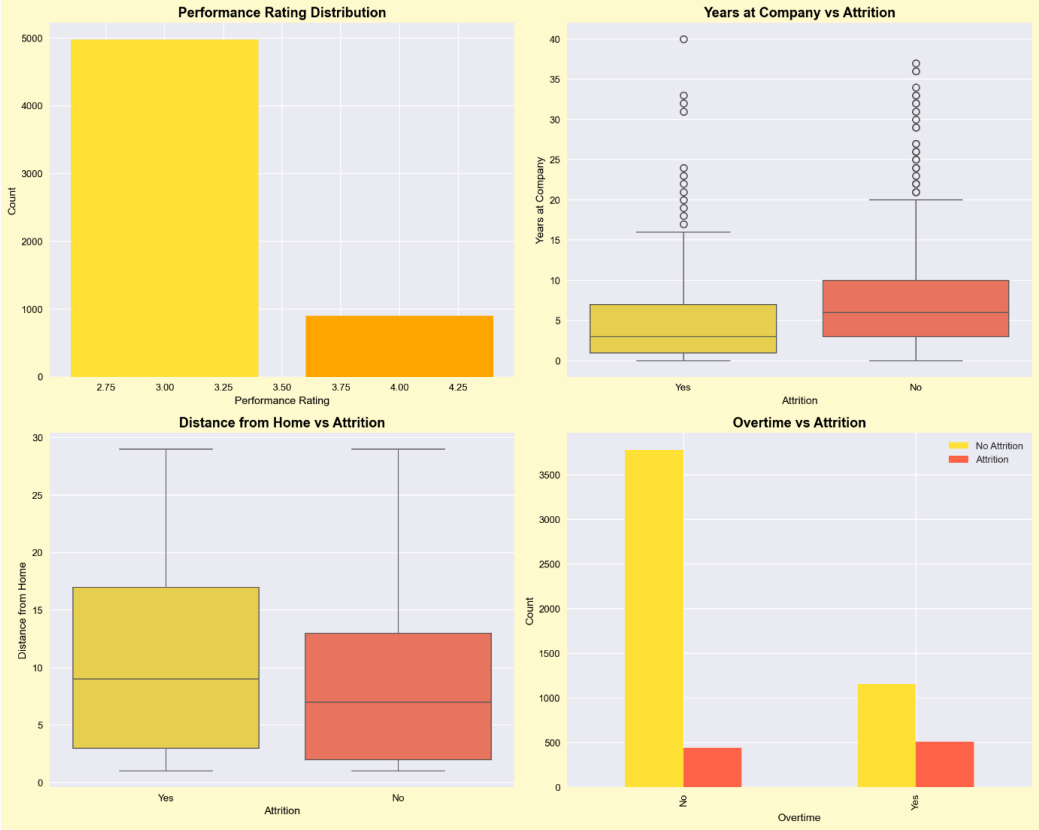
Model Integration: After selecting the best-performing model, it is serialized and integrated into the web-based system. The trained prediction model is connected with the backend application logic, enabling the system to process user input and generate attrition predictions dynamically.

Web Application Deployment: A user-friendly web application is developed using the Flask framework. The application provides an interface where HR managers or authorized users can enter driver information and obtain real-time attrition predictions. The web application handles user authentication, input data processing, model prediction, and result display.

Result Interpretation and Decision Support: The system analyzes the prediction results and categorizes drivers based on their attrition risk level. These predictions provide valuable insights for organizational decision-makers, enabling proactive workforce management strategies. By identifying drivers with high attrition risk, the organization can implement retention strategies, improve working conditions, and enhance overall operational efficiency.

4. RESULTS ANALYSIS

The results of the research demonstrate the successful implementation of an AI-driven HR attrition prediction system integrated with a Flask-based web interface. The research provides a seamless workflow from user registration to HR analytics and real-time attrition prediction. Each component, including data visualization, model training, and predictions, is presented through interactive screens and dashboards. The system allows HR managers to analyze employee trends, understand key attrition factors, and make informed decisions based on predictive analytics. Performance evaluation of different models validates the effectiveness of the chosen algorithms in predicting employee turnover accurately.



(a), (b), (c), (d)

Fig. 3: Performance and work analysis of drivers

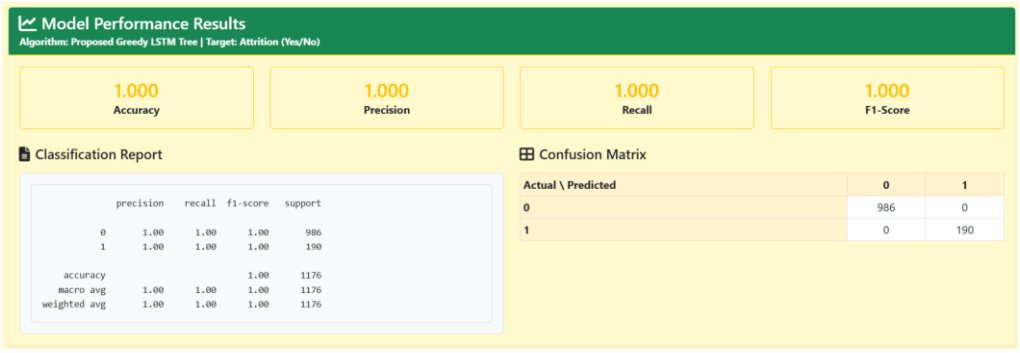
Fig. 3 presents performance-related visualizations that evaluate the relationship between driver work attributes and attrition behavior.

Fig. 3 (a) The Performance Rating Distribution chart displays the number of drivers across different performance rating levels. The bar chart representation highlights the overall performance distribution within the workforce.

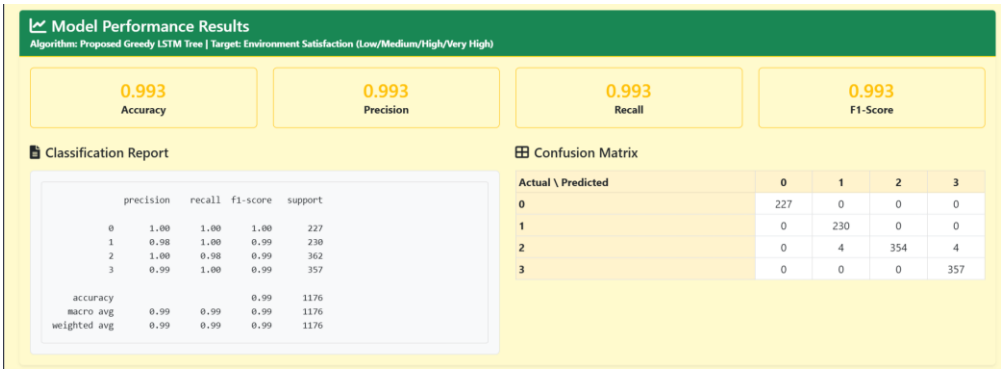
Fig. 3 (b) The Years at Company vs Attrition boxplot illustrates the relationship between driver tenure and attrition status. The visualization highlights differences in organizational experience between drivers who remain in the organization and those who leave.

Fig. 3 (c) The Distance from Home vs Attrition boxplot presents the variation in commuting distance for drivers based on attrition status. The visualization highlights how commuting distance relates to retention and separation patterns.

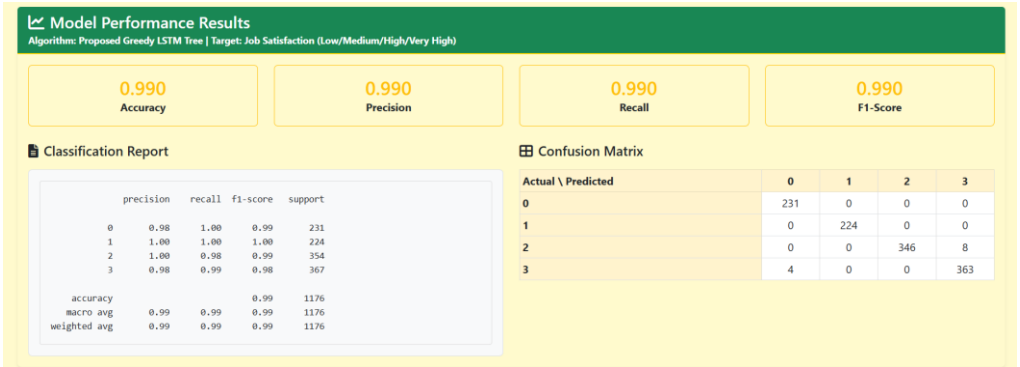
Fig. 3 (d) The Overtime vs Attrition chart illustrates the relationship between overtime work and driver attrition. The bar chart representation highlights how overtime workload influences retention and attrition patterns within the organization.



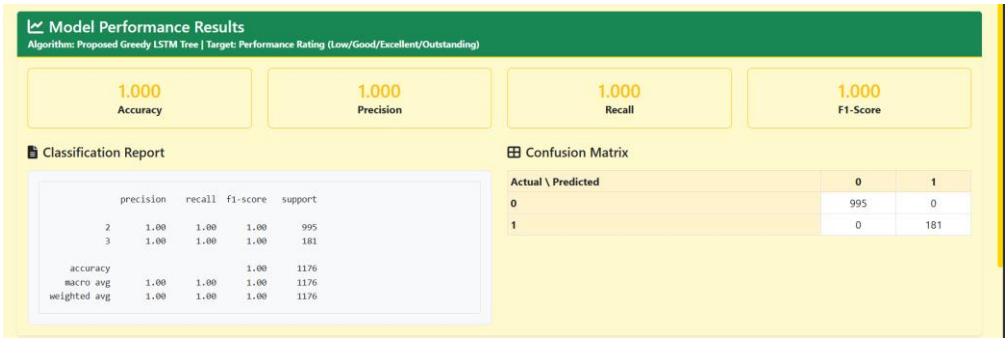
(a)


Model Performance Results
Algorithm: Proposed Greedy LSTM Tree | Target: Environment Satisfaction (Low/Medium/High/Very High)
0.993 Accuracy
0.993 Precision
0.993 Recall
0.993 F1-Score
Classification Report
precision recall f1-score support
0 1.00 1.00 1.00 227
1 0.98 1.00 0.99 230
2 1.00 0.98 0.99 362
3 0.99 1.00 0.99 357
accuracy 0.99 1176
macro avg 0.99 0.99 0.99 1176
weighted avg 0.99 0.99 0.99 1176
Confusion Matrix
Actual \ Predicted 0 1 2 3
0 227 0 0 0
1 0 230 0 0
2 0 4 354 4
3 0 0 0 357

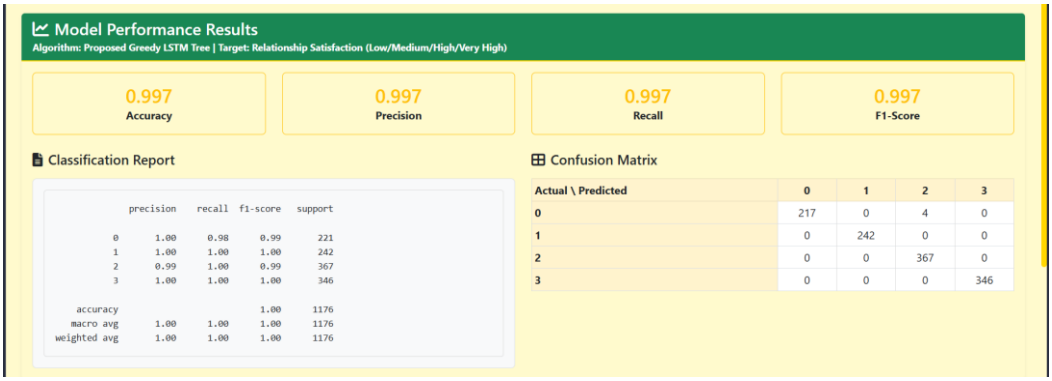
(b)


Model Performance Results
Algorithm: Proposed Greedy LSTM Tree | Target: Job Satisfaction (Low/Medium/High/Very High)
0.990 Accuracy
0.990 Precision
0.990 Recall
0.990 F1-Score
Classification Report
precision recall f1-score support
0 0.98 1.00 0.99 231
1 1.00 1.00 1.00 224
2 1.00 0.98 0.99 354
3 0.98 0.99 0.98 367
accuracy 0.99 1176
macro avg 0.99 0.99 0.99 1176
weighted avg 0.99 0.99 0.99 1176
Confusion Matrix
Actual \ Predicted 0 1 2 3
0 231 0 0 0
1 0 224 0 0
2 0 0 346 8
3 4 0 0 363

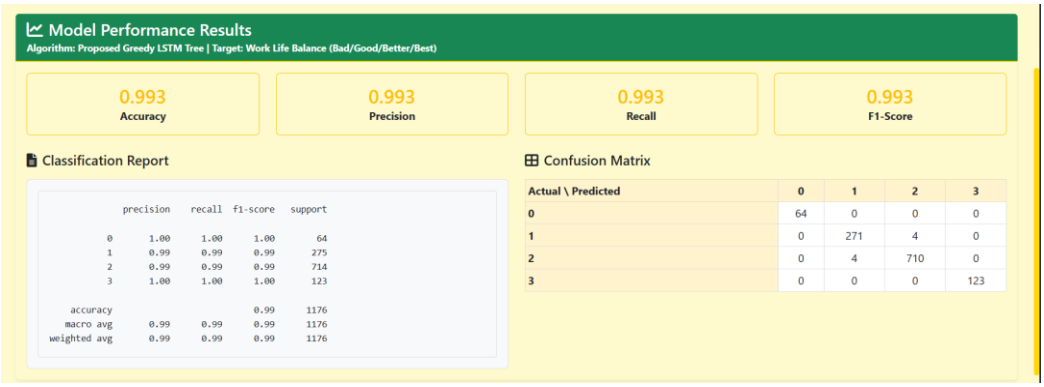
(c)



(d)


Model Performance Results
Algorithm: Proposed Greedy LSTM Tree | Target: Relationship Satisfaction (Low/Medium/High/Very High)
0.997 Accuracy
0.997 Precision
0.997 Recall
0.997 F1-Score
Classification Report
precision recall f1-score support
0 1.00 0.98 0.99 221
1 1.00 1.00 1.00 242
2 0.99 1.00 0.99 367
3 1.00 1.00 1.00 346
accuracy 1.00 1176
macro avg 1.00 1.00 1.00 1176
weighted avg 1.00 1.00 1.00 1176
Confusion Matrix
Actual \ Predicted 0 1 2 3
0 217 0 4 0
1 0 242 0 0
2 0 0 367 0
3 0 0 0 346

(e)


Model Performance Results
Algorithm: Proposed Greedy LSTM Tree | Target: Work Life Balance (Bad/Good/Better/Best)
0.993 Accuracy
0.993 Precision
0.993 Recall
0.993 F1-Score
Classification Report
precision recall f1-score support
0 1.00 1.00 1.00 64
1 0.99 0.99 0.99 275
2 0.99 0.99 0.99 714
3 1.00 1.00 1.00 123
accuracy 0.99 1176
macro avg 0.99 0.99 0.99 1176
weighted avg 0.99 0.99 0.99 1176
Confusion Matrix
Actual \ Predicted 0 1 2 3
0 64 0 0 0
1 0 271 4 0
2 0 4 710 0
3 0 0 0 123

(f)

Fig. 4: Performance and classification reports of various target attributes from GLSTMT Model (a) Attrition, (b) Environment Satisfaction, (c) Job Satisfaction, (d) Performance Rating, (e) Relationship Satisfaction, (f) Work Life Balance.

Fig. 4 presents the performance results and classification reports generated by the proposed GLSTMT model for multiple target attributes related to driver attrition analysis.

Fig. 4 (a) The Attrition classification report illustrates the model's capability to accurately distinguish between drivers who remain in the organization and those who leave. The evaluation metrics such as precision, recall, and F1-score demonstrate the strong classification performance of the proposed model in attrition prediction.

Fig. 4 (b) The Environment Satisfaction analysis evaluates the effectiveness of the proposed model in classifying satisfaction levels associated with the driver work environment. The classification report indicates accurate identification of satisfaction categories ranging from low to very high.

Fig. 4 (c) The Job Satisfaction report demonstrates the model's capability to classify driver satisfaction levels related to job roles, responsibilities, and engagement within the organization. The evaluation metrics reflect the strong predictive performance of the proposed hybrid model.

Fig. 4 (d) The Performance Rating report evaluates the classification accuracy of the GLSTMT model in predicting driver performance categories. The results demonstrate precise identification of performance levels based on historical driver attributes.

Fig. 4 (e) The Relationship Satisfaction report reflects the model's ability to classify variations in satisfaction related to relationships between drivers and management. The classification metrics highlight accurate identification of interpersonal satisfaction levels.

Fig. 4 (f) The Work Life Balance report measures the model's capability to classify drivers according to their balance between professional responsibilities and personal life. The results demonstrate the strong performance of the proposed model in identifying work-life balance levels within the driver dataset.

Attrition

Algorithm	Accuracy	Precision	Recall	F1 Score
Proposed Greedy LSTM Tree	1.0	1.0	1.0	1.0
RandomForestClassifier	0.8384	0.703	0.8384	0.7648
GradientBoostingClassifier	0.8384	0.703	0.8384	0.7648
SVC	0.8384	0.703	0.8384	0.7648

(a)

Environment Satisfaction

Algorithm	Accuracy	Precision	Recall	F1 Score
Proposed Greedy LSTM Tree	0.9932	0.9933	0.9932	0.9932
RandomForestClassifier	0.3265	0.2973	0.3265	0.2483
GradientBoostingClassifier	0.3333	0.2167	0.3333	0.2221
SVC	0.3078	0.0948	0.3078	0.1449

(b)

Job Satisfaction

Algorithm	Accuracy	Precision	Recall	F1 Score
Proposed Greedy LSTM Tree	0.9898	0.9899	0.9898	0.9898
RandomForestClassifier	0.3367	0.2095	0.3367	0.24
GradientBoostingClassifier	0.3163	0.2028	0.3163	0.1885
SVC	0.3121	0.0974	0.3121	0.1485

(c)

Performance Rating

Algorithm	Accuracy	Precision	Recall	F1 Score
Proposed Greedy LSTM Tree	1.0	1.0	1.0	1.0
RandomForestClassifier	0.8461	0.7159	0.8461	0.7755
GradientBoostingClassifier	0.8461	0.7159	0.8461	0.7755
SVC	0.8461	0.7159	0.8461	0.7755

(d)

Relationship Satisfaction

Algorithm	Accuracy	Precision	Recall	F1 Score
Proposed Greedy LSTM Tree	0.9966	0.9966	0.9966	0.9966
RandomForestClassifier	0.3401	0.4213	0.3401	0.2314
GradientBoostingClassifier	0.3206	0.2592	0.3206	0.169
SVC	0.3121	0.0974	0.3121	0.1485

(e)

Work Life Balance

Algorithm	Accuracy	Precision	Recall	F1 Score
Proposed Greedy LSTM Tree	0.9932	0.9932	0.9932	0.9932
RandomForestClassifier	0.6071	0.3686	0.6071	0.4587
GradientBoostingClassifier	0.6071	0.3686	0.6071	0.4587
SVC	0.6071	0.3686	0.6071	0.4587

(f)

Fig. 5: Model comparison screen. (a) Attrition, (b) Environment Satisfaction, (c) Job Satisfaction, (d) Performance Rating, (e) Relationship Satisfaction, (f) Work Life Balance.

Fig. 5 presents the model comparison interface that evaluates the performance of different machine learning models used in the driver attrition prediction system. The comparison includes the results of SVC, GB, RF, and the proposed GLSTMT model across multiple target attributes. The screen displays the performance metrics of each model, allowing clear comparison of classification accuracy and effectiveness for different driver-related factors.

Fig. 5 (a) The Attrition comparison screen shows the performance results of all models for predicting whether drivers remain in the organization or leave. The comparison highlights differences in accuracy, precision, recall, and F1-score values among the models, demonstrating the effectiveness of the proposed GLSTMT model in identifying driver attrition patterns.

Fig. 5 (b) The Environment Satisfaction comparison screen evaluates the classification performance of the models in identifying driver satisfaction levels related to the working environment. The comparison illustrates how each algorithm performs in distinguishing between different satisfaction categories ranging from low to very high.

Fig. 5 (c) The Job Satisfaction comparison screen displays the performance of the machine learning models in predicting job satisfaction levels among drivers. The results provide a clear view of how effectively each model classifies satisfaction levels associated with job roles, work conditions, and organizational engagement.

Fig. 5 (d) The Performance Rating comparison screen illustrates the classification results of different models in predicting driver performance levels. The comparison highlights the ability of each model to accurately identify performance categories based on driver performance attributes.

Fig. 5 (e) The Relationship Satisfaction comparison screen evaluates the models based on their performance in identifying the level of satisfaction related to relationships between drivers and organizational management. The displayed metrics provide insights into the classification capability of each model for interpersonal satisfaction factors.

Fig. 5 (f) The Work Life Balance comparison screen presents the comparative performance of the models in classifying drivers according to their balance between professional responsibilities and personal life. The results demonstrate the effectiveness of the proposed model in identifying different work-life balance levels within the dataset.

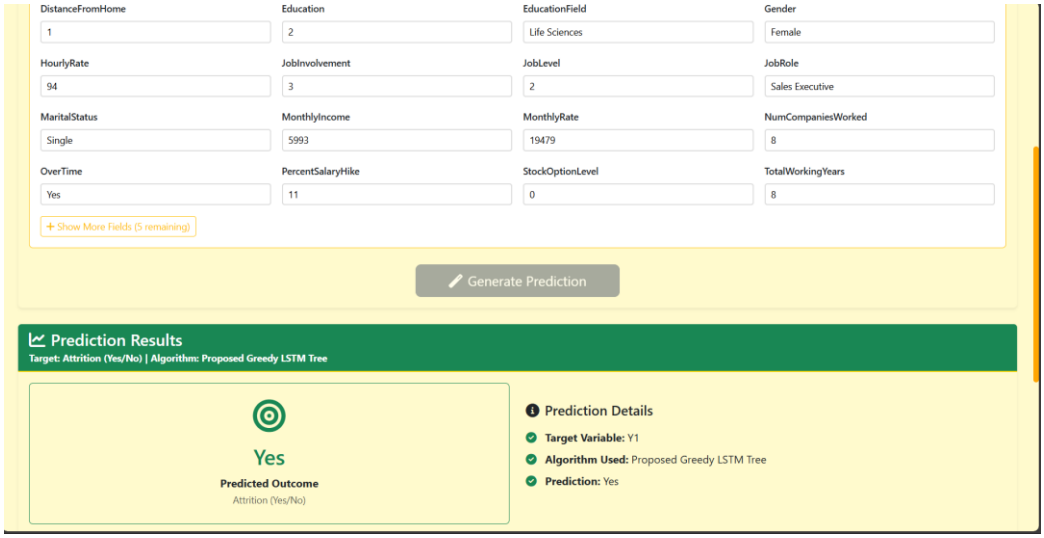


Fig.6: Predictions on test data.

The fig.6 presents the attrition results for employees, indicating the probability of leaving. HR managers receive actionable insights to identify high-risk employees and take preventive measures to reduce turnover.

5. CONCLUSION

This research successfully designed and implemented an AI-driven Employee Attrition Prediction System using Machine Learning and Deep Learning techniques. The system integrated data preprocessing, exploratory data analysis, and multiple predictive models including SVC, RF, GB, and GLSTMT. A Flask-based web application provided secure user authentication, HR analytics dashboards, and real-time prediction functionality. The experimental results demonstrated that ensemble and hybrid models achieved higher prediction accuracy compared to traditional classifiers. Visual analytics through EDA improved understanding of key attrition factors such as job satisfaction, work-life balance, and years at the company. The system enabled HR professionals to identify high-risk employees early and supported data-driven workforce management decisions. Overall, the research delivered an efficient, scalable, and intelligent solution for employee attrition analysis in real-world organizational environments.

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